Aalto University
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# How does long-term revenue growth contribute to returns on equities?

**Abstract**

Understanding business growth is important, because it has a wide range of consequences ranging from matters of everyday businesses to valuation and investing. Prediction of long-term growth is often needed, but simple extrapolation of short-term models would exclude any mechanism driving long-term alterations. This thesis aims at understanding mechanisms of long-term growth and how this growth translates into investor returns. First of all, I find that long-term revenue growth is highly skewed with big winners outperforming the rest substantially. Second, contradictory to what one would expect from digital winner-take-it-all mechanisms, this distribution does not change as a function of time. Third, results suggest that the long-term risk of investing into growing companies operates at the level of attenuating growth. Finally, investing in companies with strong negative revenue growth is associated with abnormal risk-adjusted returns of 11.6% per year.

NOVEMBER 14, 2018

BACHELOR'S THESIS IN FINANCE

Henri Blomster 531 223

## 1. Introduction

Understanding growth of companies is of key importance. Amount of future growth has a direct impact on need for financing, recruitment of staff and generation of the most optimal structure to meet the needs of company specific functions. Growth has also substantial effect on company valuation, which has importance beyond mere investor returns. For example, mergers' and acquisitions involve discussions around the fair value of the companies with both the selling and buying sides arming themselves with arguments of what is seen as fair value. In discounted cash flow -based models, future growth and used discount rate are two central components, that have a substantial effect on the final outcome of company valuation. Valuation approaches based on multiples also rely heavily on the prediction of future growth.

### A. Revenue as a measure of growth

There is a magnitude of growth-related metrics that can be studied. Amounts of users, readers or subscribers might be key metrics and of higher importance compared to revenue from the operational point of view of an individual business. Investors interests lie within earnings power and value of assets. However, there are upsides into studying the metric of revenue growth even though it would not be the actual end-point of interest. Unlike operational metrics, revenue growth is widely applicable and comparable to all kinds of businesses. Second, there are downsides for direct study of long-term earnings growth. One reason for this is non-linearity of growing earnings associated with high proportion of fixed costs. For strongly growing companies, current earnings are less important, and the more important future earnings and margins would be highly dependent on continuation of growth. Also, a company facing great investment and growth opportunities not only needs additional working capital but could also choose to aim for long-term maximal growth at the cost of short-term earnings. The long-term effect of such a situation would be continuous increase in earnings power that would be difficult to detect from the actual earnings, figure 1.

***Figure 1.*** *Simple use of earnings metric does not always capture steady long-term growth.*


Amount of assets are seldomly used as a metric for company growth, but book-to-price ratios are used as a way to identify growth stocks (Fama and French 1998). Nonetheless, within growth stocks this metric is problematic. Book-to-price is an appropriate measure in situations where assets mainly consist of factories. However, users cannot be sold nor bought at the market. Because of this they lack market price and are not considered as assets according to IFRS-rules. However, for some companies, users or subscribers are the most central asset that not only brings in revenue but also provides a protective moat.

The situation gets even more complicated because of non-linear effects related to benefits of existing users. Current users drive future user growth, provide competitional advantages and protective moat. From network theory we know that new vertices *attach preferentially* to well-connected sites and that this emergence of scaling is a universal winner-takes-it-all mechanism (Barabási and Albert 1999). Without appropriate background a reference to network theory may be challenging to grasp so I present the practical perspective through the example of Netflix. If Netflix has the highest number of subscribers, then potential customers are likely to hear first from Netflix and not the competitors. Second, cost is split between all subscribers and product is shared among all subscribers so the service provider having most subscribers has most resources and is in key position to provide the best product at the best price. In other words, the growth-driver value of subscribers is not tied to direct number of subscribers, but to the comparison of *how many subscribers compared to competitors*. Existence of these kinds of non-linear mechanisms driving genuine value of user-based assets, would make linear evaluation of user-based assets challenging.

I conclude that revenue is an appropriate measure for evaluating the big picture of growth.

#### B. The long-term effect

According to Warren Buffet, a good investment takes a long time to materialize: "If you aren't willing to own a stock for ten years, don't even think about owning it for ten minutes." However, the discipline of finance is most often interested in short term stock returns. For example, stock recommendations of financial analysts most often give 12-month target prices. In some cases, the recommendation periods are even shorter. The Finnish analyst house Inderes has a "Top3" list, that contain recommendations for a period of approximately three months. Several banks publish trading lists having recommendations aimed for very short time frame.

Although academics use long time horizons the data is often split into short time frames. For example, Malkiel (1995) studies the returns from investing in equity mutual funds using data from 1971 to 1991. This is a twenty-year period, however, the data is split very quarter and mixed after this. The reader is presented with a summary of risk-adjusted returns that seem to be normally distributed. In comparison, professor Bessembinder has studied long-term returns of individual stocks and the results imply, not normal distribution, but huge differences between individual stock returns (Bessembinder 2018). Research based on assessment of *long-term effects* of revenue growth could thus have the potential to alter our perception of it. Simple extrapolation of short-term effects may not sufficient to understand the mechanisms behind long-term alterations. This is the reason why I study long-term revenue growth.

There are certain changes that have occurred in the past decades. For example, the churn of S&P500 has increased dramatically. The average lifespan of an S&P 500 company has decreased form 90 years in 1935 to 18 years today. Another dramatical shift can be seen in the amount of intangible assets. In 1975 only 17% of assets were of intangible nature, but in 2015 as much as 84% of all assets are intangible (Hill and Elsten 2017). The previously described Netflix is only one example, where long-term growth drivers of winner-takes-it-all rely on digital products that can be distributed efficiently through the internet. Thus, one could expect that these changes in society would result in more concentrated growth. The data in this thesis, however, shows that growth has not become more concentrated than before. This highlights the importance of non-digital mechanisms driving towards the highly skewed distribution of growth.

#### C. Value versus growth

An important aspect of this thesis is to gain understanding on the connection of growth and investor returns. Both highly diversified passive investing and highly selective stock picking can be justified by the highly skewed distribution of long-term growth presented in this thesis. A third investment alternative is to seek for growth-based anomalies and find investing rules resulting in risk-adjusted abnormal excess returns.

Many academic studies have come to the conclusion that investors should avoid buying stocks of growth (Basu 1977; Fama and French 1998; Lakonishok et al. 1994; LaPorta 1996). Interestingly, most research on growth stocks originate from research based on stock price, not direct assessment of growth. Instead of using price-based sorting of stocks into baskets of "value" and "growth", I sort stocks according to actual revenue growth of the underlying companies. When interpreting the results of this specification one should keep in mind the general notion that the effect of value can be absent for, not just a year or two, but for sustained periods of time (Criddle 2013). The measurement period for my experiment is from July 1998 to end of June 2013.

Nevertheless, my results are interesting. Lakonishok et al. (1994) find that investors get overly optimistic and make the mistake of tying their expectations of future growth to past growth. LaPorta (1996) finds that analysts get excessively optimistic about high predicted earnings growth. However, within the measurement period 1998-2013 and using the long-term revenue growth approach I find evidence against such claims. In addition, when operating within the range of positive revenue growth I detect no statistically significant difference in returns between low and high revenue growth of the past.

So, *as long as we discuss cases where past long-term revenue growth stays positive*, there is no disadvantage in buying stocks with past strong revenue growth. However, a market beating strategy can be built by buying the stocks which have displayed strong *negative* long-term revenue growth in the past. This strategy beats the market with 11.6 percentages of risk adjusted abnormal returns per year. This anomaly may in part emerge from investors being overly pessimistic about past negative growth, but also from the practical limitations of actually pursuing such a strategy. These limitations are discussed in this thesis.

## 2. The research questions

The main question is how long-term revenue growth affects stock market returns. To be more specific the aim is to understand in which way long-term revenue growth *does* and *does not* contribute to investor returns.

The specific questions are as follows:

1) What is the distribution of long-term revenue growth of U.S. companies?
2) Does this distribution of long-term revenue growth change as a function of time?
3) Does distribution of long-term revenue growth explain strongly skewed distribution of long-term stock market returns described by Bessembinder (2018)?
4) Would a long-term revenue growth -based investment strategy be able to beat the market?

## 3. Data and methodology

The experiments aim, with a few alterations, to replicate the result of Bessembinder (2018). However, instead of stock-return distribution I will investigate the distribution of long-term revenue growth.

I pick all companies within NYSE, Amex, and Nasdaq exchanges revenue on start date and end date from Compustat. Start and end dates are ten years apart starting from fiscal 1957. I inflation adjust the end date revenue according to the Bureau of Labor Statistics consumer price index, to make different decades comparative. Then I count revenue growth percentage between start date and end date and map the distribution of revenue growth for each decade similar to Bessembinder (2018). To measure general skewness, I pool the data. To answer the question whether distribution of growth has changed during time, I measure the skewness of long-term revenue growth for each decade. In order to limit the effect of low starting revenue I also perform analysis where I include only companies having a starting revenue of minimum 10M USD in 1957 currency. I do inflation adjustment for this 10M initial cut-off because 10M in 1957 equals 87.9 Million in 2018.

To understand correlation between growth and investor return, I regress decade long investor returns on decade long revenue growth percentage. This means combining Compustat database with CRSP database. The merging is done through GVKEY and PermCo identifiers on using appropriate dates only. The goal with regressing returns on revenue growth is to investigate, whether skewed stock-market returns could be partly explained by skewed revenue growth of same time period. As differences in decade long revenue growth can be substantial, I do also second stage analysis. In the second stage I first sort stocks into ten baskets according to revenue growth and then measure excess returns of these baskets. I measure the statistical significance of difference of excess returns between baskets using a paired two sample for means t-test.

In search of investment strategy, I determine the effect of first sorting stocks according to long-term revenue growth and measuring the investor returns after this sorting period. For this I conduct three roll-over experiments.

For first roll-over experiment I retrieve revenue growth amount for all stocks traded in NYSE, AMEX and NASDAQ between fiscal 1990 to 1997. I then collect corresponding 1-year returns for all stocks without rebalancing from July 1998 to end of June 1999. I repeated this procedure and pooled the data with one-year intervals for 15 years i.e. with sorting periods of 1990-1997, 1991-1998 etc. with last sorting period being 2005-2012. For this roll-over experiment I did not include stocks for which data was incomplete within any given period of sorting or investor return measurement. I sorted the pooled data based on prior revenue growth and exclude stocks with negative revenue growth from analysis. Finally, I compare non risk-adjusted returns of lowest and highest revenue basket.

For second roll-over experiment, I retrieve revenue growth amount and shape for all stocks traded in NYSE, AMEX and NASDAQ between fiscal 1990 to 1997. I apply exponential trendline for annual revenues and continue with stocks having a trendline fit of at least R squared 0.975. From these I pick 100 stocks with strongest revenue growth and count next year portfolio return starting with monthly rebalancing from July after sorting period. Then I use sorting period of 1991 to 1998 and measure next year returns starting from July 1999. I continue with this annual re-allocation of capital to collect monthly portfolio returns for 15 years i.e. 180 months, and regress these portfolio returns on common risk factors (Fama and French 1993). In second version of this experiment, I do not pick strongest revenue growth, but pick the companies with total revenue growth corresponding to 20-30% annual growth and exponential trendline fit of at least R squared 0.975. I count next year returns with monthly rebalancing. In both cases the stocks in the portfolio changes every year and returns are measured for a total period of 15 years.

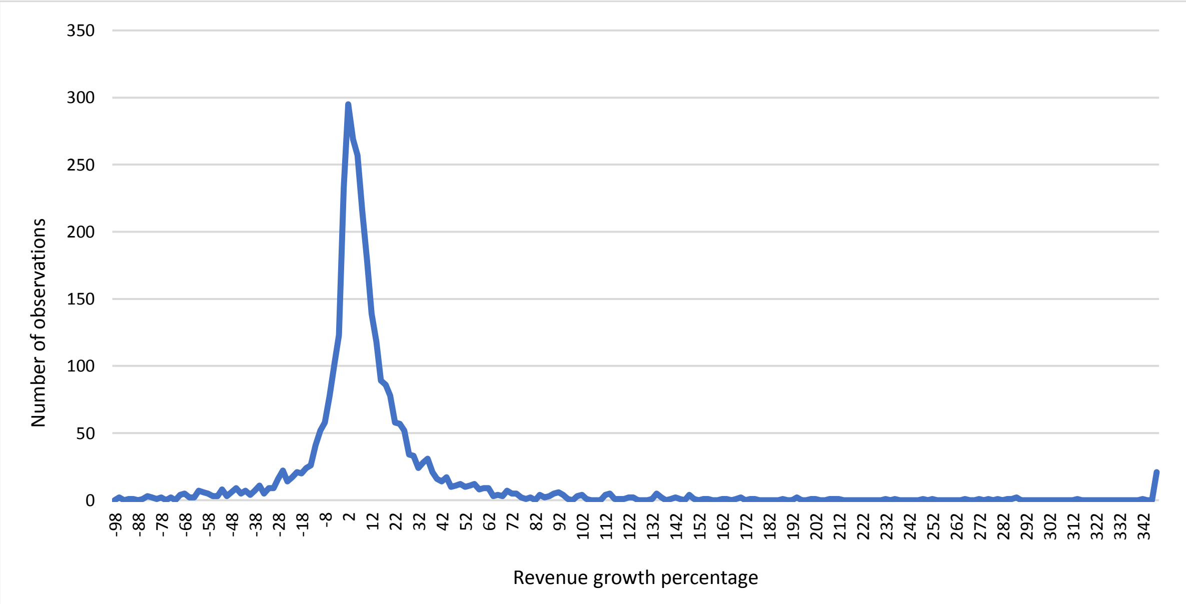
For third roll-over experiment, I retrieve revenue growth amount for all stocks traded in NYSE, AMEX and NASDAQ between fiscal 1990 to 1997. I include stocks with negative revenue growth and sort the data based on prior revenue growth into ten baskets and measure next year portfolio returns for the lowest and highest revenue growth portfolio starting from July1998, with monthly rebalancing including stocks with incomplete data on investor returns. Then I use sorting period of 1991 to 1998 and measure next year returns for these portfolios starting from July 1999. I continue with this annual re-allocation of capital to collect monthly portfolio returns for 15 years i.e. 180 months, and regress these portfolio returns on common risk factors. I also count the returns for buying the low revenue portfolio and selling short the high revenue growth portfolio and regress this against common risk factors taken from the Kenneth French's website (Fama and French 1993, Fama and French 2016). Finally, I measure one-year returns of negative revenue portfolio without monthly rebalancing and map the distribution of these returns.

## 4. Results and discussion

### A. The practical consequence of revenue growth distribution

Regardless of valuation method used, company future growth is a central component that has a substantial effect on the outcome of the valuation procedure. To explain the role of that the revenue distribution has, I start by presenting the distribution of short period revenue growth, figure 2. Similar to short-term stock returns this is normally distributed.

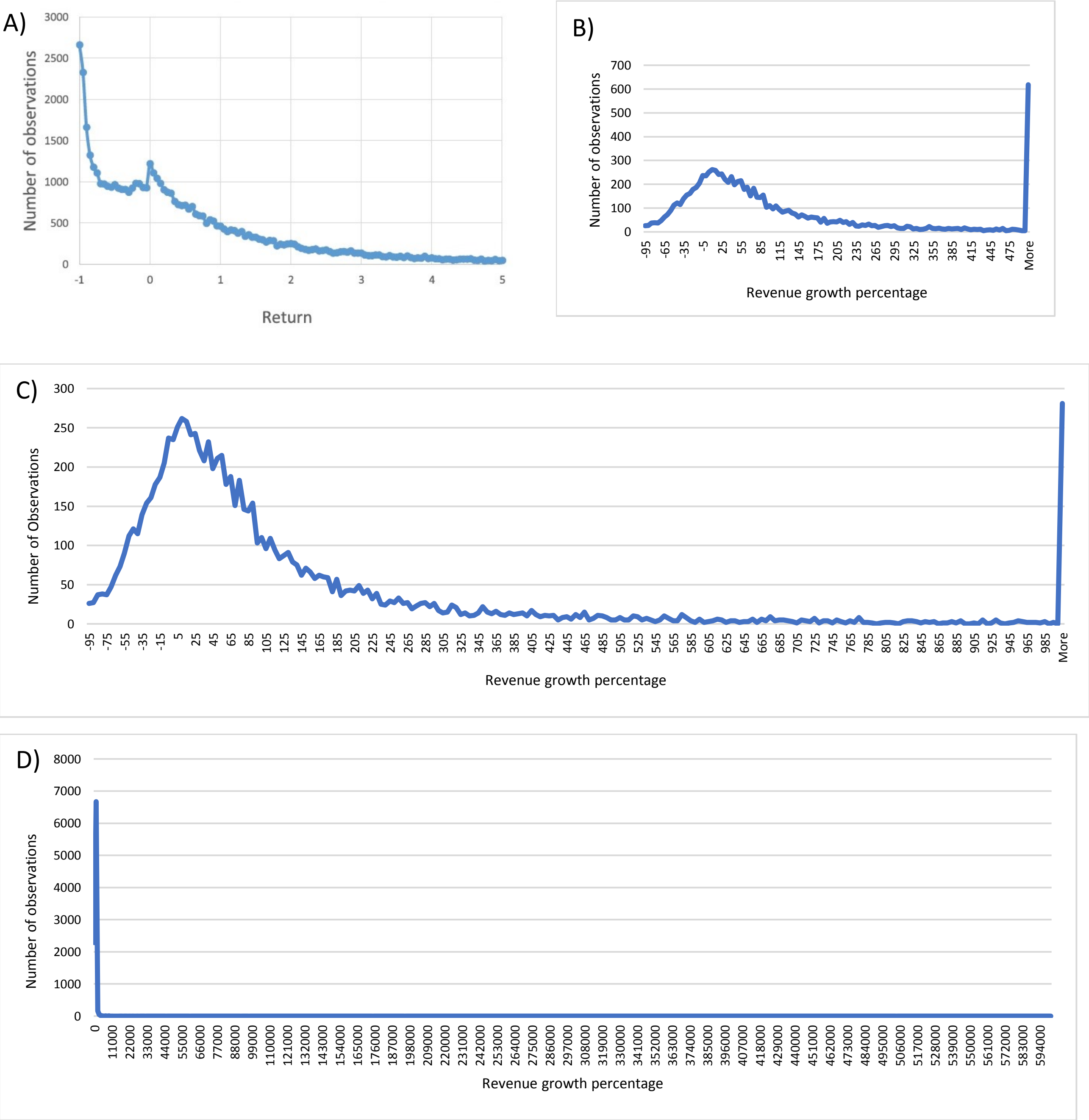
***Figure 2.*** *A histogram of single quarter long revenue growth between Q1 and Q2 of 2015. I analyzed revenue growth between first and second quarter of 2015 for the companies traded in NYSE, AMEX and NASDAQ. The distribution is approximately normal.*




For valuation analysis one would need to estimate the future growth for any given company. Now, let us assume that I have the most likely scenario in my hands. The company in question would be likely to have some very good qualities, but so would its competitors. The future growth could thus be estimated as average and be counted as the average of the relevant peer group, industry etc. adjusted by some firm specifics. The point here is that from figure 2 it would feel natural to estimate the average future growth of an average company to be the arithmetic average.

Let us now study the distribution of long-term revenue growth. This is shown in figure 3. From this figure I come to the point, that the arithmetic average is pushed up by a small number of extreme values. As a consequence, the average company would not be expected to grow with the pace of arithmetic average, but by the pace of the median. In panels B and C high peaks of "more" tell us that that there are several companies exceeding growth of both 500% and 1000% respectively. I conclude this to be a genuine strongly skewed distribution, instead of being a consequence of a couple of outlier values.

***Figure 3.*** *Comparison of long-term distributions between investor returns and revenue growth. Both are highly skewed. A) Distribution of decade long investor returns as in Bessembinder 2018. More than 20% of data points exceed returns of 500% and are not displayed in the figure. The distribution is highly skewed. B) Distribution of decade long revenue growth depicted in similar fashion as in Bessembinder 2018. I analyzed inflation adjusted decade long revenue growth for 12 decades for the companies traded in NYSE, AMEX and NASDAQ. I included only values for which Compustat data was available for the complete period of measurement. Main reason for data not being available for the whole period are events of mergers and acquisitions (data not shown). Similar to long-term stock returns, long-term revenue growth is highly skewed. The highest number of observations is for revenue growth of more than 500 percent. C) Even though the displayed amount of growth is doubled, a high number of observations do not fit to the displayed histogram. D) The actual extreme skewness of long-terms revenue growth can be seen when all data is displayed. I excluded only two most extreme values from panel D.*



Based on these results, I state that the more appropriate approximation for the average company is the *median* of the long-term growth of peers. From table 1 below one can see, that there is a clear difference between average and median for all measured periods.

**Table 1**. Decade long revenue growth is highly skewed and the difference between median and mean is substantial. I correct second time point revenue for inflation prior to counting company revenue growth. The measured growth for e.g. 1957-1966 is based on the differences between reported revenue of fiscal year 1957 and reported revenue of fiscal year 1967.

| Initial Decade | N | Mean | Median | Skewness |
|---|---|---|---|---|
| 1957-1966 | 675 | 199.1 | 83.3 | 9.3 |
| 1967-1976 | 1731 | 700.2 | 82.9 | 41.5 |
| 1977-1986 | 1871 | 534.7 | 39.4 | 39.9 |
| 1987-1996 | 2317 | 1526.9 | 64.1 | 29.7 |
| 1997-2006 | 2871 | 1233.5 | 98.5 | 29.3 |
| 2007-2016 | 2932 | 529.2 | 21.0 | 50.5 |

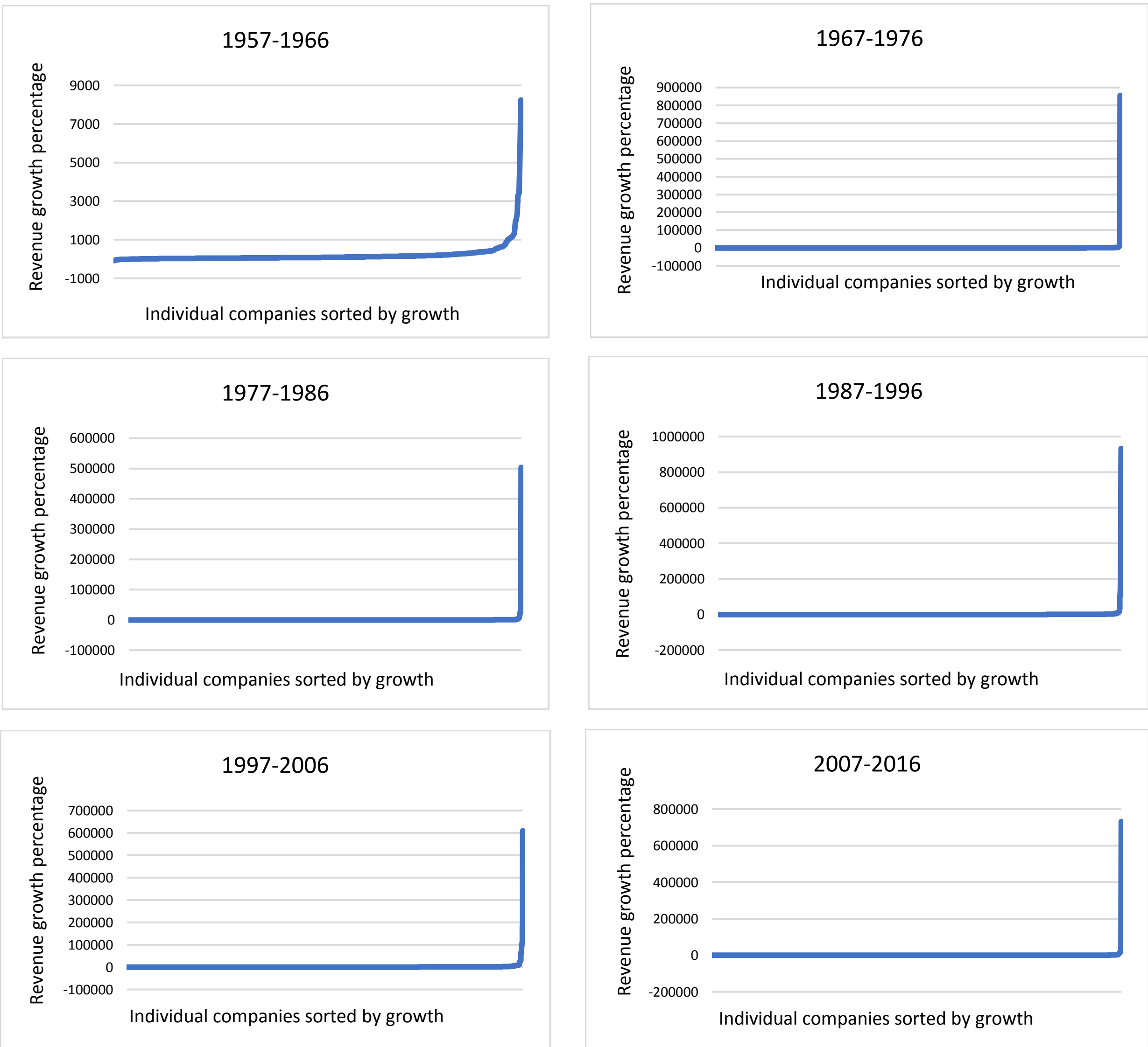
On the other hand, a strongly skewed distribution of revenue growth also means, that some companies are able to grow substantially. This implies that superior companies with strong track records and extraordinary leadership that operate on top of one or several winner-takes-it all mechanisms can grow substantially. In contrast, the short-term, normal distribution would suggest such extraordinary growth to be highly unlikely. The distribution of actual long-term revenue growth shows that extreme growth is very much possible and has always been very much possible. It is just that very few companies are capable of achieving this.

In practical terms growth is difficult to predict and analysts actually largely fail in their target price estimates. In general, analysts are overly optimistic about future growth in earnings (La Porta 1996). Second, analysts give higher recommendations to stocks, that should actually be sold and overall do a poor job in predicting stock returns (Engelberg et al. 2018). Thus, the key take-home message is to make lower growth estimates based on using median values. However, the fact that extreme values of growth have always existed, may help to understand the emergence of huge variations sometimes present for target prices of growing companies. Let me highlight how extreme this variation can be. In February 2008 CEO Catherine Wood from Ark Investment management estimated that shares of Tesla will one day hit $4000, whereas the average target price in the same month was $319. This difference is huge.

**B. The distribution of long-term revenue growth has not changed as a function of time**

In the 1970's humanity did not possess internet nor pure digital products. While many digital winner-takes-it-all mechanisms are known to exist, one could imagine that the distribution of long-term revenue growth would have changed as a function of time and that the age of internet would be associated with a more extreme distribution. However, this is not the case, figure 4. I measured decade long revenue growth for several decades starting from 1957. To visualize this distribution, I line up the companies on x-axis and sort-and-plot amount of revenue growth in percentages achieved during ten years of time. Done like this one can see extreme differences. Most companies do not grow, and some companies grow to the extreme.

***Figure 4.*** *Distribution of 10-year revenue growth as a function of time. Taking into account that Compustat has been founded in 1962, it is evident that distribution of long-term revenue growth has not changed as a function of time. All companies are on x-axis and their decade long revenue growth is displayed on y-axis. I correct second time point revenue for inflation prior to counting company revenue growth. The measured growth for e.g. 1957-1966 is based on the differences between reported revenue of fiscal year 1957 and reported revenue of fiscal year 1967.*



However, the problem with this simple experiment is, that it includes companies with very low starting revenue. The problem with low starting revenue, is that modest amount in total revenue could lead to drastic differences when counted as difference in percentages. Because of this problem I redo the previous analysis with one distinction. For 1957 I include only companies that have a revenue of at least 10 million USD. For later decades I apply the same filter, but with inflation adjustment, figure 5 and table 2. Without inflation adjustment, the cut-off level would be totally different starting at 1957 compared to starting from 2007, The results are presented in figure 5 and table 2.

***Figure 5.*** *Distribution of long-term revenue growth has not changed as a function of time. I include only companies having a starting revenue of minimum 10M USD in 1957 currency. Long time periods include substantial effect of inflation, so I do inflation adjustment for this 10M USD initial cut-off. Overall growth relies on a very small number of companies. All companies are in a line on x-axis and their decade long revenue growth is displayed on y-axis. I correct second time point revenue for inflation prior to counting company revenue growth. The measured growth for e.g. 1957-1966 is based on the differences between reported revenue of fiscal year 1957 and reported revenue of fiscal year 1967.*

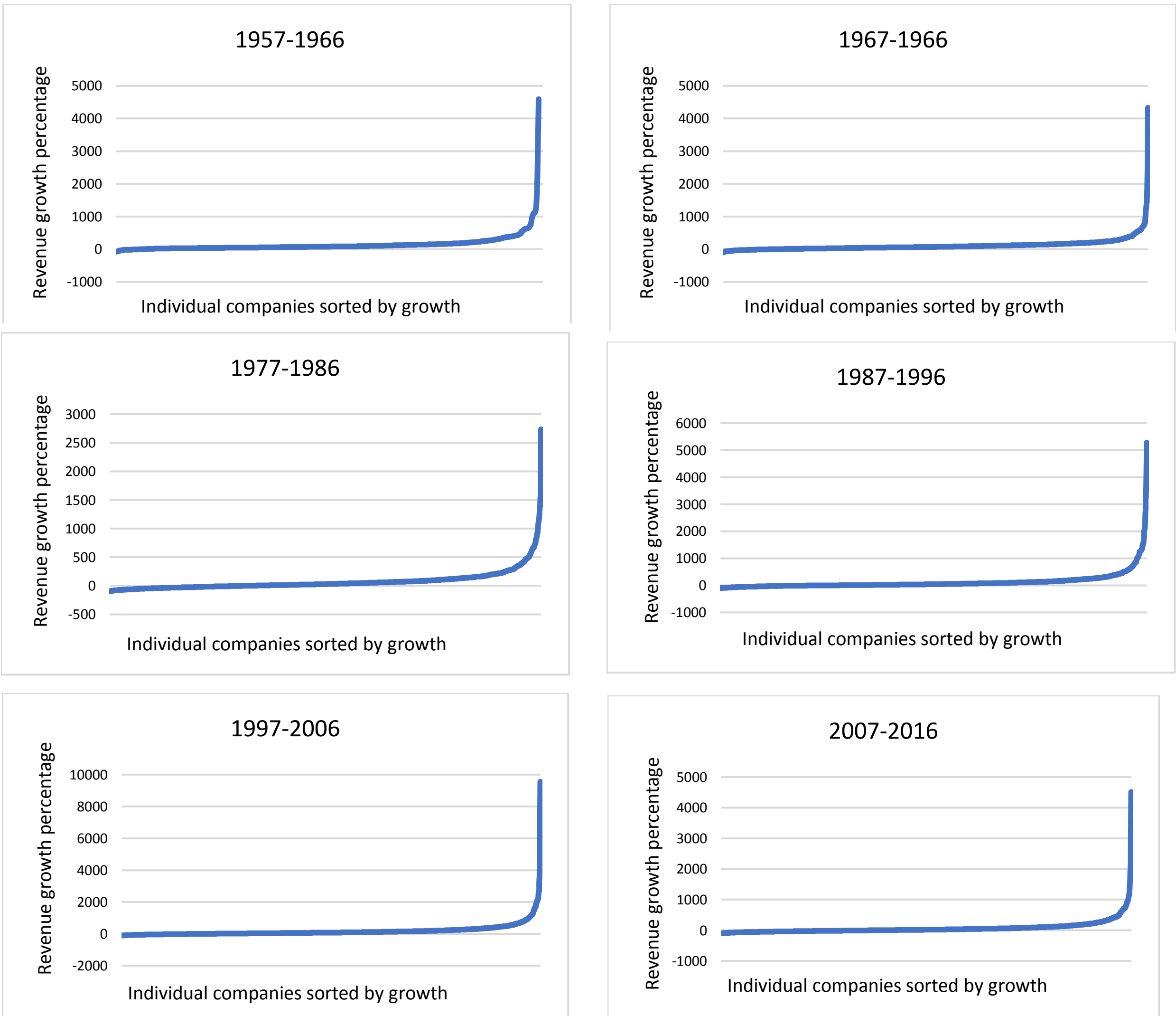


**Table 2**. Decade long revenue growth is highly skewed and the difference between median and mean is substantial. I correct second time-point revenue for inflation prior to counting company revenue growth. The measured growth for e.g. 1957-1966 is based on the differences between reported revenue of fiscal year 1957 and reported revenue of fiscal year 1967. Only companies having a starting revenue of minimum 10M USD in 1957 currency are included. This cut-off limit is inflation adjusted for later time points. Skewness drops as a result of applying the start revenue cut-off but is still substantial.

| Initial Decade | N | Mean | Median | Skewness |
|---|---|---|---|---|
| 1957-1966 | 640 | 146.1 | 80.6 | 9.0 |
| 1967-1976 | 1442 | 114.2 | 71.9 | 9.8 |
| 1977-1986 | 1473 | 77.2 | 29.6 | 5.2 |
| 1987-1996 | 1644 | 127.4 | 42.7 | 7.3 |
| 1997-2006 | 2003 | 186.5 | 82.2 | 10.6 |
| 2007-2016 | 2306 | 71.7 | 18.6 | 8.5 |

From figure 5 one can visually observe that there is no difference in the distribution of growth between the different decades. From table 2 one can see the same result in numerical format. The skewness of the distribution stays roughly the same between the decades. What is quite clear, and contrary what one might expect, is that there is no observable shift when going from eras before internet to eras where internet and digital products became prominent.

Thus, although media present headlines talking about the power of internet giants and winner-takes-it-all-economies, digital platforms and the importance of FAANG stocks, the times are in reality not that different. We live and have always lived in a winner-takes-it-all-economy. The mechanisms driving this structure may have changed form with time and technological development, but the structure itself has always been there.

### C. Distribution of revenue growth does not explain the emergence of skewness in returns

An argument can be made that psychological factors and sentiment affect stock prices in the sort run. For example, media pessimism induces downward pressure on stock prices (Tetlock 2007). However, this effect is transient. Long-term investor returns are based on fundamentals and the market prices reflect intrinsic values of stocks (Sharpe 1964).

Regarding appreciation of intrinsic company value, there are limits to how much margins can be increased. Margins could improve from 5% to 15% but continuing to 90% does not seem plausible. Therefore, the hypothesis is that huge investor returns from individual stocks as seen by Bessembinder 2018, would have to be accompanied by strong revenue growth.

However, a simple regression between long-term stock returns and long-term revenue growth suggests that this is not the case, table 3.

**Table 3.** Revenue growth does not explain the emergence of extreme skewness in long-term stock returns. I count decade long revenue growth and total investor returns for the same period for the eras of 1957-1966, 1967-1976, 1977-1986, 1987-1996, 1997-2006 and 2007-2016. I pool the data and regress total investor returns on amount of revenue growth. Although p-value of 0.029 is below 0.05 one has to keep in mind the extremely low value of R Square and the coefficient of 0.001.

| *Regression Statistics* | |
|---|---|
| Multiple R | 0.0227 |
| R Square | 0.0005 |
| Adjusted R Square | 0.0004 |
| Standard Error | 381.822 |
| Observations | 9233 |

| | *Coefficients* | *Standard Error* | *t Stat* | *P-value* |
|---|---|---|---|---|
| Intercept | 145.67 | 3.98 | 36.63 | 1.93E-274 |
| Growth Inflation adjusted | 0.001 | 0.000 | 2.18 | 0.029 |

Figure 8 visualizes the same data. One can observe extreme investor returns without extreme revenue growth. On the other hand, one can observe extreme revenue growth without extreme investor returns. In conclusion, strongly skewed distribution of long-term revenue growth does not directly explain the emergence of strongly skewed long-term stock returns.

However, the result does not mean that realized revenue growth would be unimportant for investor returns. I show details of two data points with high investor returns and low revenue growth in figure 9. Breaking down decade long revenue growth and comparing this to investor returns of same time period suggests that realized revenue growth is important for investor returns. However, the relationship is not a simple one-to-one correlation and includes the problem of scale.

***Figure 8.*** *Distribution of long-term revenue growth does not explain the emergence of extreme skewness in distribution of long-term stock returns. I count decade long revenue growth and total investor returns for the same period for the eras of 1957-1966, 1967-1976, 1977-1986, 1987-1996, 1997-2006 and 2007-2016. I pool and visualize this data. A) This panel show all available data points. Blue arrows show that extreme investor returns can be obtained with modest revenue growth. Grey arrows show that strong revenue growth does not always lead to strong investor returns. Highlighted companies MB = Monster Beverage, C = Concord EFC, J = Jefferies Financial GRP. B) Here I present the same data as in A, but with the distinction of cutting most extreme values out. Both axes are cut at 6000. Again, strong revenue growth is not a prerequisite for strong investor returns (blue arrows) and vice versa (grey arrows).*

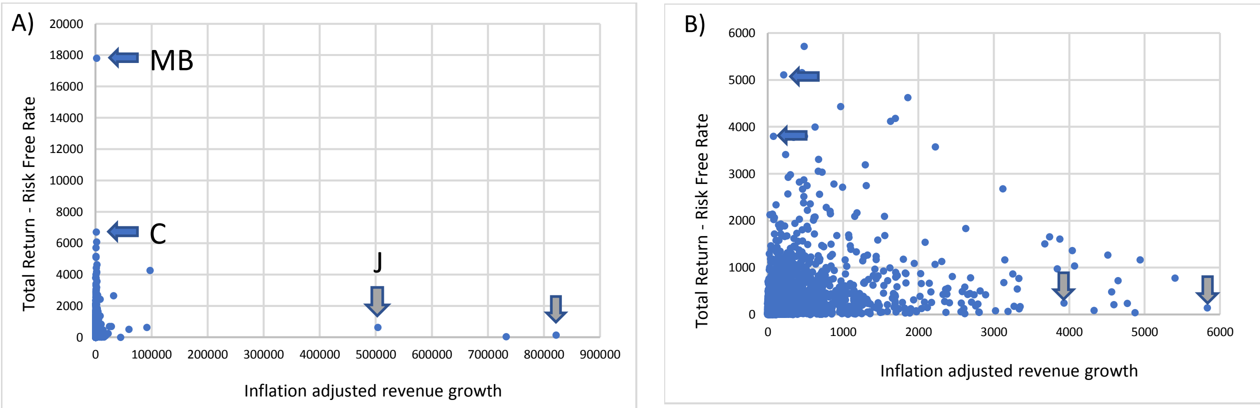
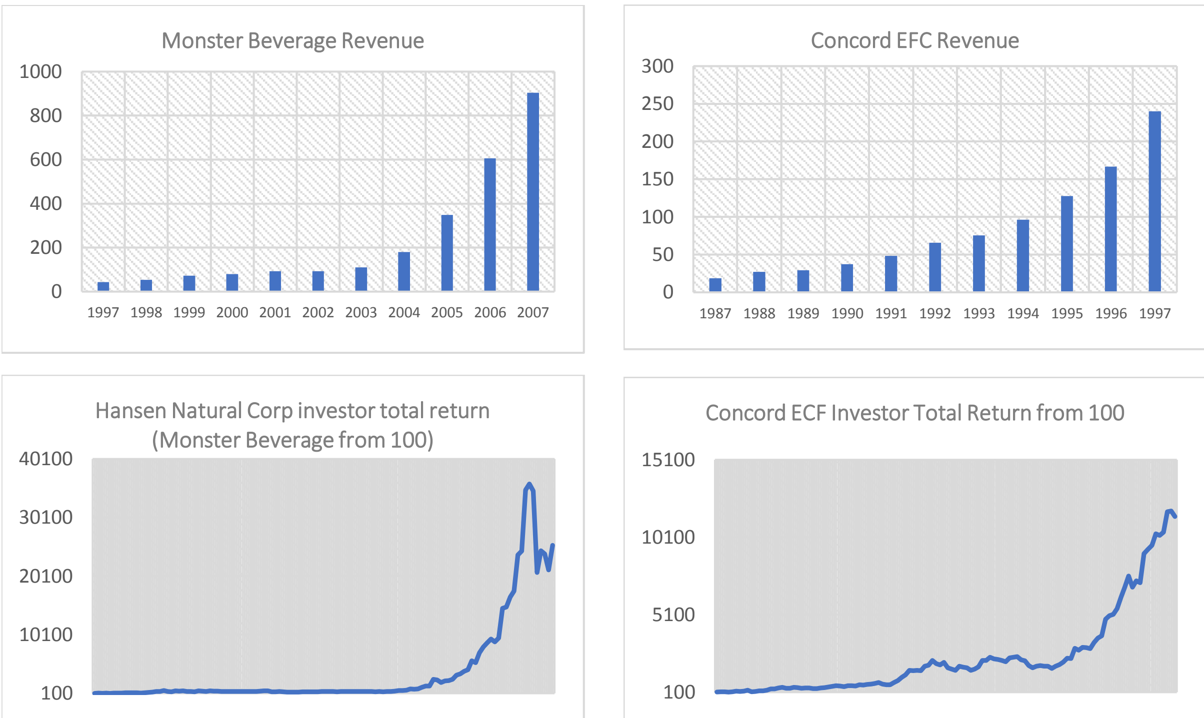
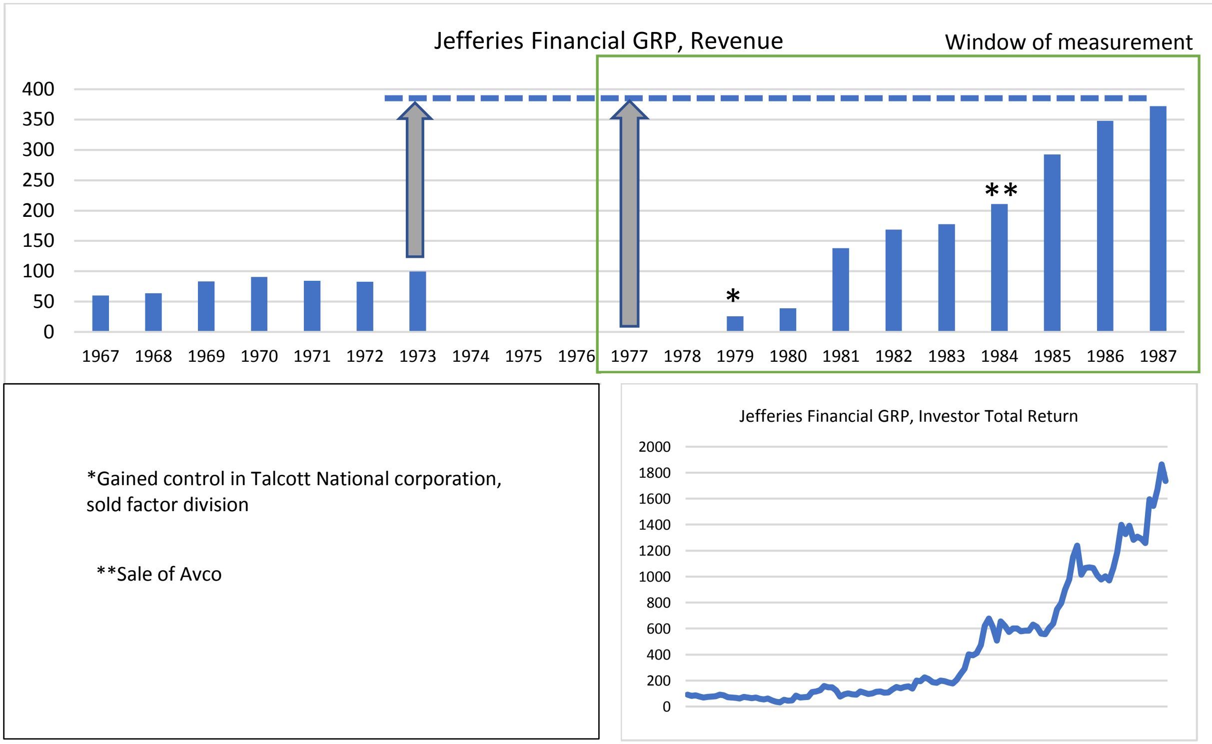



***Figure 9.*** *Problems of simple regression. I dig deeper to understand extreme outcomes. The shape of revenue and investor returns of both Monster Beverage (MB in figure 8A) and Concord EFC (C in figure 8A) suggest that lack of correlation is due to differences in magnitude.*



Situations where extreme revenue growth does not result in extreme investor returns can also be partly explained by methodological limitations, as explained in figure 10.

***Figure 10.*** *I show the example of Jefferies Financials (marked with J in figure 8A) to highlight why extreme revenue growth does not necessarily lead to extreme investor returns. First, starting with values close to zero can lead to extreme growth numbers. This can be accompanied by a previous drop in revenue. Second, measured revenue growth does not always indicate organic growth, but can also be affected by both selling and buying of other companies.*



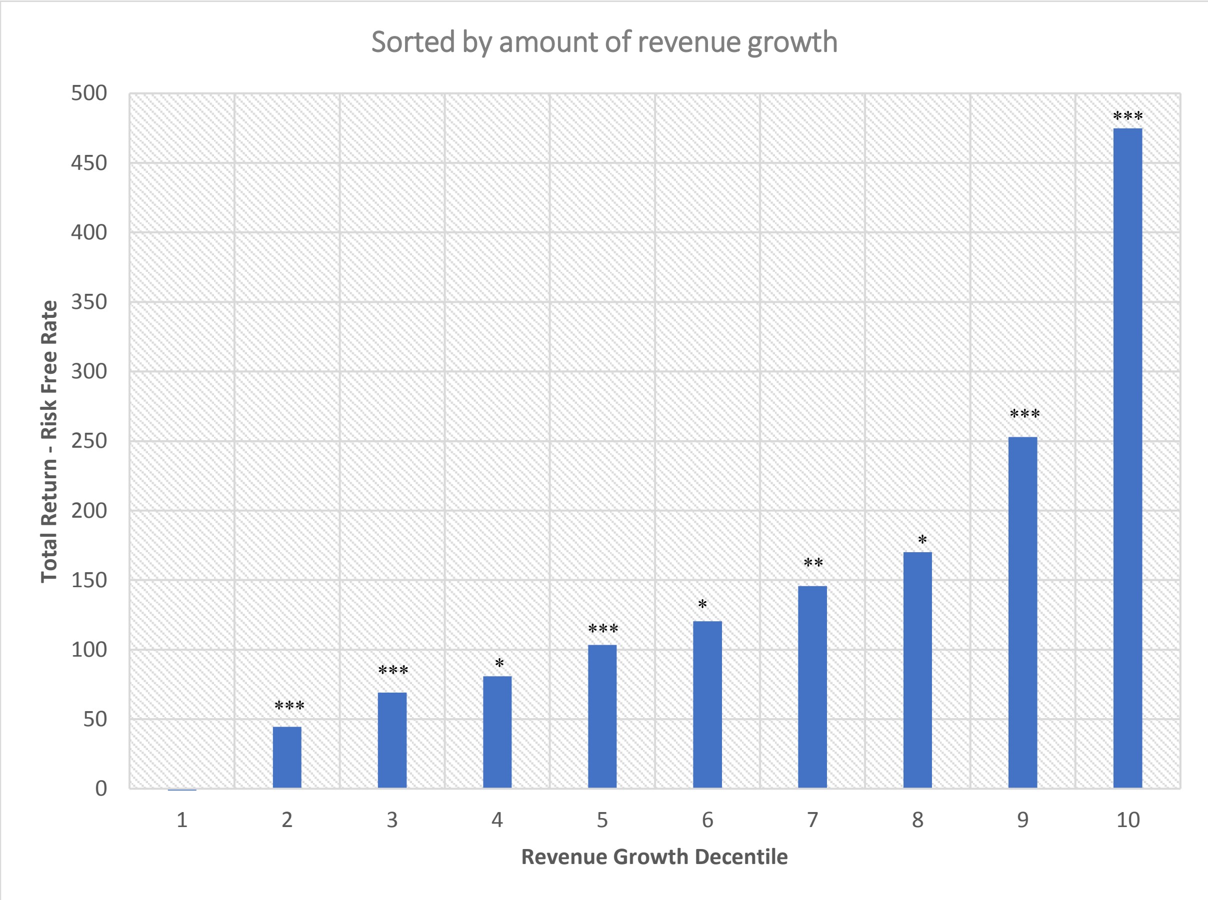

To summarize the analyzes presented in this section, I conclude that highly skewed long-term stock returns as presented by Bessembinder (2018) do not emerge as a simple and direct consequence of highly skewed distribution of long-term revenue growth.

**D. The correlation between long-term revenue growth and investor returns**

To investigate the relationship between long-term revenue growth and investors returns in a way that circumvents the obvious problems associated with the simple regression approach, I collect both realized revenue growth and investor returns for stocks in NYSE, AMEX and NASDAQ for six decades starting in 1957. This data is then pooled and sorted into baskets according to revenue growth. Subsequently, I measure returns on each of these baskets.

The advantage with this approach compared to direct correlation, is that it compresses extreme values close to each other. Second, unlike taking of logarithm, negative numbers are compatible with this sorting experiment. The results are presented in figure 11.

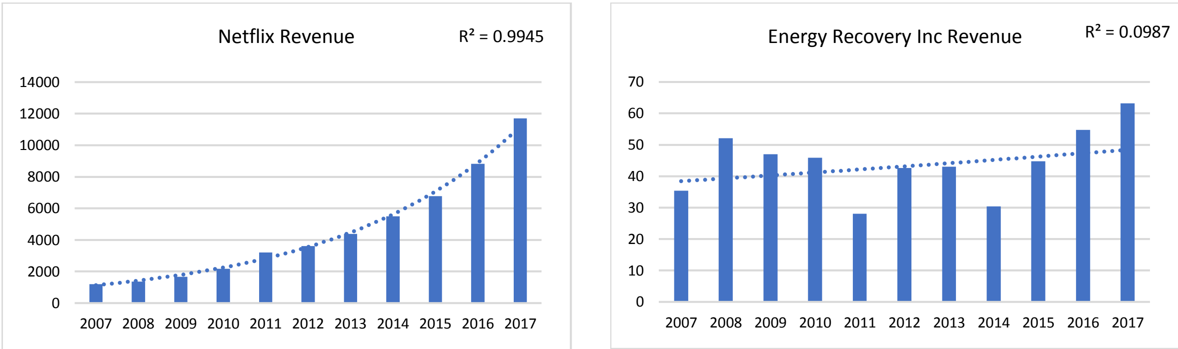
***Figure 11.*** *Amount of revenue growth correlates with realized investor return within the same time window. I measure decade long revenue growth and investor returns subtracted with risk free rate for a decade long period from 1957-1966, 1967-1976, 1977-1986, 1987-1996, 1997-2006 and 2007-2016. I sort portfolios according to realized amount of decade long revenue growth. This analysis helps to understand the correlation between realized returns and revenue growth and does not correlate past growth with future returns. Stars flag statistical significance compared to previous deciles. One star above decile four indicates that it is greater than decile three with p <0.05, two stars indicate p<0.01 and for three stars indicate p< 0.001.*




From figure 11 we see that there is a strong correlation between realized revenue growth and stock returns. During the time when growth occurred the basket of stocks with highest revenue growth yielded 475% compared negative 3.6% of basket with lowest revenue growth.

As pointed out in figure 10, issues arise from simple comparison of revenues between year one and ten years after. For example, starting values close to zero and one-time events caused by mergers and acquisitions can cause high values of revenue growth, without corresponding strong organic growth. One way to correct for these issues is to also consider the shape of revenue growth. This can be done by drawing an exponential trendline through annual revenues and counting the fit of that trendline as explained in figure 12.

***Figure 12.*** *Illustration of the concept of "shape of growth". Both companies grow, but growth of Netflix is smoother. High R squared relates to smooth growth and low R squared relates to a bumpy road of growth.*




Using this technique, I should be able to remove one-time events and include only companies with real organic growth into the analysis. As a result, I would expect to obtain a stronger effect for revenue driving stock returns. This is indeed the case. Basket of stocks that contain most strong and most even revenue growth yields returns of 813%. This is more than 475% of returns obtained from sorting stocks only on amount of revenue growth, table 4 and figure 11.

***Table 4****. Realized revenue growth and revenue shape both correlate with realized investor return within the same time window. I measured decade long revenue growth, shape of this growth and corresponding investor returns for a decade long period from 1957-1966, 1967-1976, 1977-1986, 1987-1996, 1997-2006 and 2007-2016. For amount of total investor returns, I subtracted risk free rate prior to analysis. I pooled the data and sorted the stocks first into deciles according to R Squared value of exponential trendline fitted to annual revenues. Subsequently I shorted the stocks in each decile into quintiles based on the amount of realized revenue growth i.e. growth percentage. This analysis helps to understand the correlation between realized returns and revenue growth and does not correlate past growth with future returns. Higher realized revenue growth results in higher investor returns in all R Squared deciles, i.e. investors are rewarded for higher realized revenue growth regardless of the shape of revenue growth.*

| N= 9233 | R Squared decile | | | | | | | | | | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Revenue Growth Quintile | -2.8 | 38.2 | -6.8 | -0.8 | 12.1 | 53.2 | 51.5 | 88.7 | 105.2 | 129.3 | 46.8 |
| | 18.9 | 36.6 | 42.4 | 63.1 | 92.8 | 120.0 | 113.2 | 129.3 | 141.7 | 181.0 | 93.9 |
| | 65.9 | 71.6 | 60.1 | 97.8 | 100.3 | 156.3 | 123.2 | 158.5 | 196.2 | 201.1 | 123.1 |
| | 55.9 | 60.2 | 68.7 | 110.3 | 129.1 | 148.2 | 174.9 | 268.2 | 279.3 | 304.4 | 159.9 |
| | 78.7 | 57.4 | 84.0 | 123.5 | 182.0 | 239.8 | 437.0 | 443.9 | 589.6 | ***812.9*** | 304.9 |

There is a difference. The direct correlation between revenue growth and investor returns is weak even *during the era when this growth occurs*, but ability to select stocks with strongest long-term revenue growth, would result in superior returns, figures 8 and 11. Now although there are technical explanations to why correlation is low when done directly and strong when using the sorting approach, we should not discard the actual result: the relationship between revenue growth and investor return is mainly of non-linear nature. This big picture should be kept in mind when using revenues to drive costs and earnings in discounted cash-flow models. One natural explanation for non-linearity arises from the relationship between scaling, high fixed costs and earnings, but skewed distribution of growth could also give rise to comparative mechanisms.

Let us speculate on such a comparative non-linear mechanism. Assume that I own five stocks in the same competitive space and that these companies would be somewhat comparable. Initially I follow short-term growth, which in turn is driven by seasonality, one-time effects and pure luck. Eventually long-term growth shows a clear difference of one company growing faster than the others. Instead of only including the different growth rates into to my discounted cash flow model I see this track-record as a signal of a superior business model. Knowing about the winner-takes-all distribution I sell the other four companies and buy the one that grows the most. This signal would emerge regardless of the actual amount of revenue growth, let it be 10, 20 or 30 percent annually. As the winning company continues to outperform the others more and more investor reaches this conclusion, pushing up the price of the winner. Because of this competition-based preferential attachment -kind of mechanism the other four face selling pressure even though their growth continues for the time being. As a result, 20% annual growth of one company could signal for selling, whereas the 25% annual growth of the other company could signal for buying. These kinds of non-linear mechanisms reaching beyond discounted cash flow models could explain the emergence of low linear correlation between long-term revenue growth and investor returns.

Now, for such a non-linear mechanism to exist, investors would need to actually make comparisons of growth within a space with widely known winner-takes-it-all mechanism. Social media with users benefitting from other users should be such a space. It is easy to find media and investment analysis articles containing direct user growth comparison between Snap Inc owned Snapchat and Facebook owned Instagram Stories (data not shown). Thus, we know that at least in isolated situations, investors compare growth rates. In summary, with this data I cannot exclude, nor prove, the presence of genuine comparison-based non-linear mechanisms driving the relationship between realized growth and investor returns.

#### E. Risk and pricing of halting growth

Previous experiments show how realized revenue growth affect the returns of those investors who are lucky enough to keep the companies that grow. However, growth cannot continue in eternity and eventually growth stops. Naturally, in real life attenuating growth affects investor returns because amount of future growth is difficult to predict.

To study the effect of attenuating growth I first sort stocks according to seven years of growth and wait half a year to be sure that this realized growth is known to the public and included in stock prices. Then I buy the stocks, keep them for one year and measure non risk-adjusted investor returns, table 6. Lakonishok et al. (1994) find that the investors' mistake of tying their expectations of future growth to past growth results in poor future returns. However, I find no difference between high and low revenue growth portfolios as long *as only positive revenue growth values are included*. This result suggests that continuation of revenue growth is prized in correctly.

**Table 6**. Investors are not overly optimistic about past revenue growth. I retrieve revenue growth amount for all stocks traded in NYSE, AMEX and NASDAQ between fiscal 1990 to 1997. I then collect corresponding returns from July 1998 to end of June 1999 for all of these stocks. I repeated this procedure and pooled the data with one-year intervals for 15 years i.e. with sorting periods of 1990-1997, 1991-1998 etc. with last sorting period being 2005-2012. I did not include stocks for which data was incomplete within any given period of sorting or investor return measurement. Stocks with positive revenue growth were sorted into ten baskets and returns of lowest and highest revenue basket were compared. There is no significant difference in non-risk adjusted returns between portfolios of high and low prior revenue growth.

| t-Test: Paired Two Sample for Means | *High Growth* | *Low growth* |
|---|---|---|
| Mean | 14.4 | 16.4 |
| Variance | 5874.3 | 3736.3 |
| Observations | 4018 | 4018 |
| Pearson Correlation | 0.017 | |
| Hypothesized Mean Difference | 0 | |
| df | 4017 | |
| t Stat | -1.30 | |
| P(T<=t) one-tail | 0.096 | |
| t Critical one-tail | 1.65 | |
| P(T<=t) two-tail | ***0.192*** | |
| t Critical two-tail | 1.96 | |

As pointed out in the previous section, long-term revenue growth can be affected by one-time effects and genuine organic growth is probably captured to a higher degree, when also the shape of revenue growth is included. Also, one could argue that even shape of past growth could signal the existence of persisting growth drivers, like network effect and benefits of having the biggest digital platform. Therefore, it is of interest to study future returns of stocks displaying the shape of even past revenue growth. For this I include a selection criterion, where the fit of an exponential trendline for past seven years has to equal an R squared value of at least 0.975. From these stocks I pick the two portfolios. The first portfolio contains 100 stocks with highest past revenue growth, table 7. The second portfolio contains stocks with past revenue growth between 20-30% a year, table 8. Taking common risk factors into account, neither of these portfolios contain significant negative nor positive alpha. This result indicates that attenuating revenue growth is prized in correctly by the markets and that the average investor would not win nor lose by buying stocks with previous strong revenue growth.

**Table 7.** Investing in strong past growth does not result in poor returns in the future. In this roll-over experiment I retrieve revenue growth amount and shape for all stocks traded in NYSE, AMEX and NASDAQ between fiscal 1990 to 1997. I apply exponential trendline for annual revenues and continue with stocks having a fit of at least R squared 0.975. From these I pick 100 stocks with strongest revenue growth and count next year portfolio return with monthly rebalancing starting from July after sorting period. Then I use sorting period of 1991 to 1998 and measure next year returns starting from July 1999. I continue with this annual re-allocation of capital to collect monthly portfolio returns for 15 years i.e. 180 months, and regress these portfolio returns on common risk factors (Fama and French 1993). I find no significant negative alpha. One star denotes significance at p <0.05, two stars at p<0.01 and three stars at p< 0.001. P-values are shown in parenthesis.

| Row | Alpha | Mkt-RF | SMB | HML | Adj. R Square |
|---|---|---|---|---|---|
| 1 | 0.004* | 1.120*** | | | 0.83 |
| | (0.027) | (6.59E-71) | | | |
| 2 | 0.005 | | 0.718*** | | 0.19 |
| | (0.208) | | (6.34E-10) | | |
| 3 | 0.008 | | | -0.148 | 0.002 |
| | (0.074) | | | (0.253) | |
| 4 | 0.002 | 1.059*** | 0.402*** | 0.197*** | 0.88 |
| | ***(0.120)*** | (2.50E-76) | (7.01E-16) | (3.86E-5) | |

**Table 8.** Investing in strong past growth does not result in poor returns in the future. In this roll-over experiment I retrieve revenue growth amount and shape for all stocks traded in NYSE, AMEX and NASDAQ between fiscal 1990 to 1997. I apply exponential trendline for annual revenues and continue with stocks having a fit of at least R squared 0.975. From these I form a portfolio of stocks with total revenue growth corresponding to 20-30% annual growth and count next year portfolio returns with monthly rebalancing starting from July after sorting period. Then I use sorting period of 1991 to 1998 and measure next year returns starting from July 1999. I continue with this annual re-allocation of capital to collect monthly portfolio returns for 15 years i.e. 180 months, and regress these portfolio returns on common risk factors (Fama and French 1993). One star denotes significance at $p < 0.05$, two stars at $p<0.01$ and three stars at $p< 0.001$. P-values are shown in parenthesis. With these specifications I find no significant positive nor negative alpha.

| Row | Alpha | Mkt-RF | SMB | HML | Adj. R Square |
|---|---|---|---|---|---|
| 1 | 0.004 | 1.199*** | | | 0.73 |
| | (0.160) | (2.89E-53) | | | |
| 2 | 0.005 | | 0.796*** | | 0.18 |
| | (0.312) | | (1.95E-09) | | |
| 3 | 0.008 | | | -0.194 | 0.004 |
| | (0.118) | | | (0.187) | |
| 4 | 0.002 | 1.126*** | 0.451*** | 0.181* | 0.78 |
| | ***(0.426)*** | (6.12E-53) | (1.28E-09) | (0.014) | |

In the final specification, I investigate risk-adjusted returns of ignoring shape of growth and simply buying the strongest revenue growth of the past. Earlier studies of Basu (1977), Fama and French (1998), Lakonishok et al. (1994) and LaPorta (1996) suggest that investors should avoid buying past growth, but my results do not support this conclusion. On the contrary, with the last specification and within this measurement period 1998-2013 I even find a small, yet significant positive alpha associated in buying most strong growth of the past, table 9.

**Table 9.** Buying strong long-term revenue growth of the past does not result in poor returns in the future. In this roll-over experiment I retrieve revenue growth for all stocks traded in NYSE, AMEX and NASDAQ between fiscal 1990 to 1997. I include stocks with negative revenue growth and sort the data based on prior revenue growth into ten baskets and measure next year portfolio returns for the highest revenue growth portfolio starting from July 1998, with monthly rebalancing including stocks with incomplete data on investor returns. Then I use sorting period of 1991 to 1998 and measure next year returns starting from July 1999. I continue with this annual re-allocation of capital to collect monthly portfolio returns for 15 years i.e. 180 months, and regress these portfolio returns on common risk factors (Fama and French 1993). One star denotes significance at p <0.05, two stars at p<0.01 and three stars at p< 0.001. P-values are shown in parenthesis. Buying past strong revenue growth leads to small, but significant abnormal risk-adjusted returns.

| Row | Alpha | Mkt-RF | SMB | HML | Adj. R Square |
|---|---|---|---|---|---|
| 1 | 0.008** | 1.255*** | | | 0.79 |
| | (0.001) | (1.18E-62) | | | |
| 2 | 0.008 | | 1.002*** | | 0.28 |
| | 0.064 | | (1.01E-14) | | |
| 3 | 0.012* | | | -0.363* | 0.03 |
| | (0.014) | | | (0.0138) | |
| 4 | 0.006** | 1.137*** | 0.620*** | 0.071 | 0.89 |
| | (0.001) | (5.979E-73) | (5.45E-25) | (0.178) | |

##### F. Practical implications of revenue growth distribution for investors

Let us first consider the situation of an index investor. The highly skewed distribution of revenue growth suggests that only a small number of companies experience strong long-term revenue growth. An index investor would own a small piece of "all" companies and in this way ensures owning growth at the time when growth actually occurs and gets some of the yields presented in figure 11. This is in line with the findings of Bessembinder (2018), that only a few stocks are responsible for the stock market equity premium and that this benefits the index investor. An active long-term investor might not include the best yielding stocks in the active portfolio, which could then lead to inferior returns.

Assuming that a manager believes in possessing the ability to genuinely do a better job than the market in identifying companies with high long-term revenue growth potential, a highly skewed distribution also merits for a strategy with high focus and low diversification based on identifying the long-term winners of growth. If winner takes it all, then one would want to identify the winner. Obviously to identify the winner one would need comparative analysis aimed at identification of the winner. In practical terms this means comparing several companies within the same analysis. However, most traditional stock analyses still focus on one company at a time. Yes, competitive environment, strategy and business model are often a part of the analysis, but the goal of the analysis is still to determine a 12-month target price. As a result, the individual investor aiming at identification of winners of long-term growth finds little support in the content of analysts' reports *not aimed at comparative analysis of growth*. Also, the general success of the target price approach is low (Engelberg et al. 2018).

Interestingly, one the best performing mutual funds domiciled in Finland, HCP Focus, invests for the long-term in only 8-15 companies. The idea is that if even one these picks are among the biggest winners, then the overall return will beat the market. One of the central theses of this fund is the existence of winner-takes-it-all mechanisms. As part of analysis to identify winners, HCP focus, to at least some extent, compares long-term growth of the competitive space (Grönblom 2017). HCP focus has had the highest Sharpe ratio among all mutual funds marketed in Finland and has been rated best among funds in its own class.

The results in this thesis do not yield tools to identify long-term growth in advance not even provide any evidence that long-term growth could be identified in advance. However, the results could help focused low diversified growth investors to avoid making further mistakes related to fluctuating stock prices and investor psychology. The highly skewed distribution also suggest that there is potential benefit in comparative analysis based on analyzing long-term metrics of not one, but several companies, within the same analysis.

#### G. Negative revenue growth predicts future stocks returns

The analyzes presented in the previous section concentrated on stocks with positive revenue growth and herein I find little difference in returns after strong or weak revenue growth. However, the situation changes when stocks with negative revenue growth are included. Choosing stocks with most negative long-term revenue growth seems to be a market beating strategy, table 10. Naturally, I also measure the returns of a low-high portfolio that is sorted according to long-term revenue growth. Short selling of high-growth stocks does not improve the strategy, which is in line with the results presented in the previous chapter, table 11.

Together tables 10 and 11 suggest for a strategy consisting of buying stocks with most negative long-term revenue development. Within the measured time period such a strategy would have yielded an excess return of 0.97% per month controlling for common risk factors.

This effect is robust and is not lost upon addition of additional risk factors. Adding RMW and CMA factors to the regression does not alter the amount of measured excess returns, table 12.

**Table 10**. Negative long-term revenue predicts investor returns. In this roll-over experiment I retrieve revenue growth amount for all stocks traded in NYSE, AMEX and NASDAQ between fiscal 1990 to 1997. I include stocks with negative revenue growth and sort the data based on prior revenue growth into ten baskets and measure next year portfolio returns for the lowest revenue growth portfolio (negative) starting from July 1998. I do monthly rebalancing including stocks with incomplete data on investor returns. Then I use sorting period of 1991 to 1998 and measure next year returns starting from July 1999. I continue with this annual re-allocation of capital to collect monthly portfolio returns for 15 years i.e. 180 months, and regress these portfolio returns on common risk factors (Fama and French 1993). One star denotes significance at $p < 0.05$, two stars at $p < 0.01$ and three stars at $p < 0.001$ and p-values are shown in parenthesis.

| Row | Alpha | Mkt-RF | SMB | HML | Adj. R Square |
|---|---|---|---|---|---|
| 1 | 0.013*** | 1.096*** | | | 0.72 |
| | (-1.35E-06) | (1.08E-50) | | | |
| 2 | 0.013** | | 0.849*** | | 0.24 |
| | (0.002) | | (1.78E-12) | | |
| 3 | 0.016*** | | | 0.004 | -0.01 |
| | (0.0008) | | | (0.975) | |
| 4 | 0.010*** | 1.013*** | 0.616*** | 0.412*** | 0.84 |
| | (9.75E-07) | (7.14E-60) | (1.30E-21) | (2.56E-11) | |

**Table 11**. Negative long-term revenue predicts investor returns. In this roll-over experiment I retrieve revenue growth amount for all stocks traded in NYSE, AMEX and NASDAQ between fiscal 1990 to 1997. I include stocks with negative revenue growth and sort the data based on prior revenue growth into ten baskets and measure next year portfolio returns for the lowest and highest revenue growth portfolio starting from July 1998, with monthly rebalancing including stocks with incomplete data on investor returns. Finally, I count the returns for buying the low revenue growth portfolio and selling short the high revenue growth portfolio. I repeat the procedure with sorting period of 1991-1998 and measurement period from July 1999 to end of June 2000. I continue like this to collect portfolio returns for 15 years, i.e. 180 months. These returns are then regressed on common risk factors. One star denotes significance at $p < 0.05$, two stars at $p < 0.01$ and three stars at $p < 0.001$.

| Row | Alpha | Mkt-RF | SMB | HML | Adj. R Square |
|---|---|---|---|---|---|
| 1 | 0.005** | -0.159*** | | | 0.10 |
| | (0.004) | (7.17E-06) | | | |
| 2 | 0.005** | | -0.153** | | 0.05 |
| | (0.005) | | (0.001) | | |
| 3 | 0.004* | | | 0.367*** | 0.29 |
| | (0.019) | | | (7.09E-15) | |
| 4 | 0.004** | -0.124*** | -0.005 | 0.341*** | 0.34 |
| | (0.006) | (7.28E-05) | (0.910) | (5.40E-13) | |

**Table 12**. Negative long-term revenue predicts investor returns. I retrieve revenue growth amount for all stocks traded in NYSE, AMEX and NASDAQ between fiscal 1990 to 1997. I include stocks with negative revenue growth and sort the data based on prior revenue growth into ten baskets and measure next year portfolio returns for the lowest revenue growth portfolio (negative) starting from July1998, with monthly rebalancing including stocks with incomplete data on investor returns. Then I use sorting period of 1991 to 1998 and measure next year returns starting from July 1999. I continue with this annual re-allocation of capital to collect monthly portfolio returns for 15 years i.e. 180 months, and regress these portfolio returns on common risk factors (Fama and French 2016). One star denotes significance at p <0.05, two stars at p<0.01 and three stars at p< 0.001 and p-values are shown in parenthesis.

| Row | Alpha | Mkt-RF | SMB | HML | RMW | CMA | Adj. R Square |
|---|---|---|---|---|---|---|---|
| 1 | 0.013*** | 1.096*** | | | | | 0.72 |
| | (1.35E-06) | (1.08E-50) | | | | | |
| 2 | 0.013** | | 0.849*** | | | | 0.24 |
| | (0.002) | | (1.78E-12) | | | | |
| 3 | 0.016*** | | | 0.004 | | | -0.01 |
| | (0.0008) | | | (0.975) | | | |
| 4 | 0.020*** | | | | -1.062*** | | 0.31 |
| | (9.29E-07) | | | | (3.34E-16) | | |
| 5 | 0.017*** | | | | | -0.347 | 0.01 |
| | (0.0003) | | | | | 0.07908 | |
| 6 | 0.010*** | 0.993*** | 0.567*** | 0.269** | -0.158 | 0.172 | 0.84 |
| | (1.82E-06) | (8.38E-47) | (1.33E-15) | (0.001) | (0.073) | (0.118) | |

These results suggest that investors could earn 11.6% abnormal excess returns per year by buying stocks with long-term negative revenue development. The benefits of such a strategy is that it does not include short selling and therefore does not have the costs nor limitations associated with short selling.

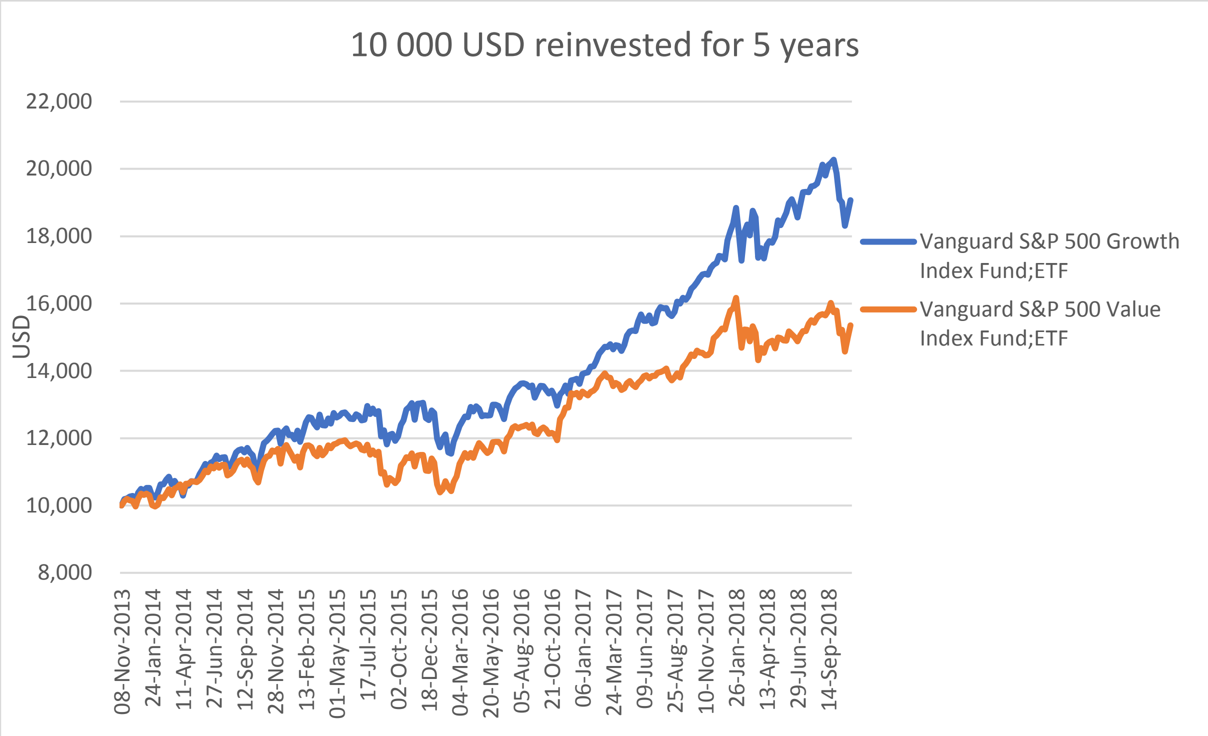
However, there are reasons why many investors would not choose to pursue this strategy. Let us first speculate on what kind of stocks are picked up by this sorting method. This method selects for compounded effect of negative revenue growth. Thus, one would expect it to contain companies that have had troubles for years. Such a situation could rise from a previously well working business model that has been unable to stand the test of time and where leadership have not been able to adapt to the changing environment. Stockmann would be a prime example of such a company. As the company delivers disappointing results year after year, more and more investors lose faith and leave to never return. The stock price keeps steadily depreciating eventually generating a substantial upside for the situation where company management finally succeeds in re-structuring the company to meet modern needs of the market. The results in table 10 and 12 suggest that the market underestimates this kind of potential of company resurrection.

The downside with a strategy buying long-term revenue growth losers is that many of those companies would continue on their path to misery. Thus, for the strategy to be functional one would have to be able to achieve broad diversification to ensure including the few companies that manage to turn around. In order to ensure broad enough diversification, the investor would need, besides data, a substantial investable space. For example, number of stocks listed in Finland would probably not be sufficient. In summary, the abovementioned limitations would likely rule out most private persons from utilizing the strategy of buying long-term negative revenue growth. Institutions, on the other hand, could theoretically pursue the "buying long-term negative revenue growth"-strategy. Associated problems relate to finding a paying clientele for such a strategy and second for the effect being robust once set out of sample.

**H. Anomalies tend to lose effect in the long run**

Naturally lost effect is problem for all reported anomalies. For example, the paper from (Lakonishok et al 1994) shows robust results on a diversity of value strategies outperforming the market during the sample period of 1963 to 1999 with 10-11% in extra returns per year. However, if we split the S&P500 index into segments of value and growth and follow the development for the last ten years the value segment yields 12% in annual return and the growth segment yields 16% in returns. For the last five years the value segment has yielded 8,7% annually compared to the 13,1 % of the growth segment. This is the opposite of what would be expected from (Lakonishok et al 1994), figure 13. Of note, five years is a long time for an active money manager. Suppose, that you run an active fund. Even though you would be able to beat the market in the long run, I do estimate that there is no way that you would able to keep your job if you start with a losing streak of five years.

***Figure 13.*** *Comparison of investing if value and growth segments of S&P500 through index-following ETF's for the last five years. The underlying style indices divide the complete market capitalization of S&P500 into value and growth segments based on ratios of price-to-book, price-to-earnings and price-to-sales. Contrarian to what would be expected from a magnitude of academic publications, the growth segment has provided higher investor returns. I downloaded the dividend including total returns data from Thomson Reuters Eikon database.*




Moreover, these are several issues with comparisons based on splitting an index in value and growth segments, like done in figure 13. The growth segment of S&P500 has a 41.3% weighting in technology, whereas the corresponding weight in the value segment is only 7.1%. Similarly, the value segment of S&P500 is highly enriched in financials. (Colas 2018). However, segmenting of common indexes into value and growth represent examples of real-life investing opportunities. For example, several ETF's are based on the S&P500 value segment and iShares S&P500 value ETF alone has net assets of 15.55 billion U.S. dollars. Suhonen et al. (2016) have studied actual trading strategies used by global investment banks and they detect a 73% deterioration of Sharpe ratios associated with real-life use of backtested strategies. These kinds of "it does not work in practice"-issues with published anomalies could be one reason for why analysts in general seem to ignore anomaly buy and sell signals in their recommendations (Engelberg et al. 2018).

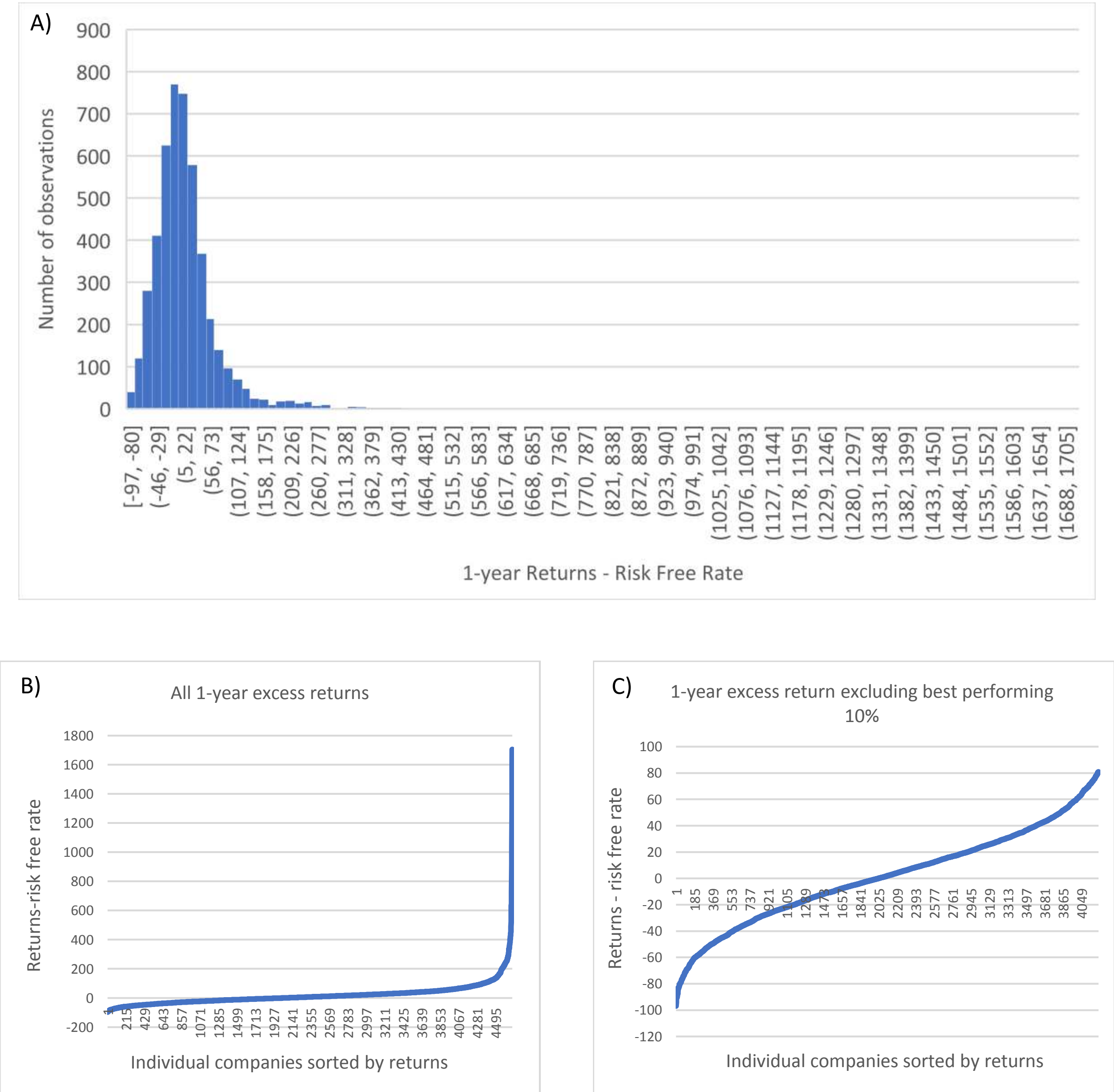
The aspect that I would like to highlight from the data presented in this thesis, is that in this particular experimental setting and time period the traditional academic effect of value is evident only where revenue growth is negative, i.e. in this data I see no excess returns related to buying stocks with only little past long-term revenue growth compared to stocks with extreme past long-term revenue growth. This result is different from example that of (Basu 1977) where an increase in excess returns are seen across decreasing price-to-earnings ratios. Also, Lakonishok (1994) reports descending returns across deciles when switching from value towards growth using a range of criteria i.e. book-to-market, cash-flow-to-market, earnings-to-price and growth rate of sales within the sample period from the end of April 1963 to the end of April 1990. The result also differs from Criddle (2013) who using a sample from February 2003 to December 2012, in contrast to Basu 1977, detects no excess returns related to low price-to-earnings ratios.

**I. There is likely to be a reason for why anomalies are not reflected in analysts' prices**

Understandably academics do not appreciate the results of stock analysts. The paper from Engelberg et al. (2018) finds that analyst information actually contributes to mispricing. By generating and analyzing an anomaly index of 125 published anomalies, the authors find that analysts price targets and recommendations predict the opposite of published anomalies. It seems that anomalies are right, and analysts wrong: the analysts' recommendation have predictive power of stock returns, but in the wrong direction. Thus, the conclusion of the Engelberg paper is that analysts are overlooking a "a good deal of valuable anomaly-related information". Based on that argumentation one could conclude that published anomalies, like the effect found in this thesis, should help analysts in the future to do a better job. Next, I will provide some arguments why this is not necessarily the case.

As I see it, the anomaly shown in tables 10 and 12, is based on mispricing of troubled companies succeeding in making a turn. So, I study the distribution of this fraction and take a closer look at the future one year returns of stocks with most negative long-term revenue development. This is the fraction of stocks that yielded the abnormal risk-adjusted returns. For this I did not include stocks for which data was incomplete within any given period. The skewed distribution of the returns of this strategy means that few winners are responsible for the overall returns of this set of stocks and that most stocks contribute less to the returns, figure 14. Now assume I am an analyst rating any of these companies and let us also make assumptions that I would know about this anomaly in advance and that the anomaly would work during this particular time period. I would also see a 10% probability that the company that I analyze would succeed in making a turnaround during the next year and that there would be significant upside in case this happens. However, I would most likely base my analysis in the 90% probability that the turnaround does not happen and maybe only write a sideline about a positive scenario. Probably other analysts would think in the same lines, because ignoring the positive turnaround gives the highest probability of correct result for the single stock analysis. Interestingly, average returns drop significantly from 18.9% per year to 1.4%, when the best performing 10% of companies are left out, figure 14.

***Figure 14.*** *The difficulty of transferring anomalies into target prices of single stocks. A) Histogram of one-year future excess returns for the portfolio of stocks with most strong negative long-term revenue growth. B) Same data in A but displayed differently. I sorted the stocks with most negative long-term revenue growth according to ascending excess returns. The stocks are on the x-axis and the returns are on the y-axis. C) Same as in B, but without the best performing 10%. Transferring the anomaly of most negative long-term revenue growth into single stock target prices would be challenging, because of the high skewness of the distribution and the strong dependence of the average on small number of extreme outcomes.*



In summary, there are several challenges in incorporation of the long-term negative revenue growth anomaly into target prices of individual stocks. First, the analyst would face the aspect of anomaly losing effect or anomaly not working during the forecasting period. Second, the skewed distribution of returns within the turnaround stocks would imply that even though the anomaly would work as a whole, the analyst would face significant challenges in applying it at the level of individual stocks.

## 5. Conclusions

There are several reasons why one would expect growth to be more concentrated than before. This is most related to the increased connectedness of the world. Previously and with physical limitations you would buy the best price-to-quality ratio in town. Now internet and globalization allow one to seek for the best price-to-quality ratio in the world. In this thesis, I study the distribution of growth and find it to be highly skewed, with a small number of companies being responsible for most of the overall long-term revenue growth. However, and interestingly, I do not notice that this distribution would change as function of time. It seems, that such a distribution has always existed in the economy, suggesting that the emergence of digital giants and FAANG stocks is not that different after all.

As a practical consequence of this distribution comes the notion on how to predict future revenue growth. The results suggest, that as long as we are not dealing with companies of genuinely extraordinary qualities, we should not expect the average long-term revenue growth, but instead accept the substantially lower value of median long-term revenue growth. A second surprising finding is the absence of direct linear connection between the highly skewed long-term revenue distribution and the highly skewed distribution of long-term stock returns. Although partly technical, this result implies that highly skewed stock returns as found by Bessembinder (2018) does not emerge directly from strong differences of long-term revenue growth. Even though there is no direct effect, pooling of stocks according to revenue growth shows that there is a significant pay-off for owning stocks of growth. The way the markets price in this premium, is at the level at halting growth: own stocks while they grow, and you will be rewarded, buy stocks that have grown in the past and this reward is almost completely lost due to companies losing their growth potential.

This result may seem trivial, but it may help investors to avoid mistakes. Owning growth companies for a short period is not expected to pay off, growth companies may be quite volatile and stock prices react to a number of events, not just attenuation of long-term growth. Thus, investors who for some reason believe in their ability to predict long-term revenue growth based on things like disruptive non-mature markets, superior and disruptive business models, superior comparative track-record of growth, superior leadership and lack of agent problems, may want to avoid costs of trading and concentrate on whether the story of long-term growth is intact or not.

Several studies of value investing suggest, that investors are overly optimistic about the future prospects of growth companies. As a result, growth companies get overpriced and earn poor investor returns. In my measurement period from July 1998 to end of June 2013, I do not notice such an effect. Investors buying companies with strong revenue growth in the past are not doing worse compared to those investors who buy slowly growing companies. However, I notice an effect suggesting that investors should buy companies with most negative long-term revenue development. Such a strategy would have yielded annual abnormal returns of 11,6%.

I propose that companies facing severe structural challenges and proven disability to adapt to changing market environments are, on average, underpriced and that this underpricing leaves substantial upside in case the company manages to get structural changes in place and get back on track. However, only a small proportion of these companies are able to turn the ship. Thus, one would need to be able to properly diversify the investments to be able to benefit from this underpricing. Even with proper diversification one would face the risk of partial or complete disappearance of this mispricing.

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